Research Article

Linear Regression Analysis Results of the CGM Sensor PPG Comparison Between Predicted PPG Data Using the Linear Elastic Glucose Theory (LEGT) and Measured PPG Data During a ~2-year COVID-19 Quarantine Period for a type 2 Diabetes Patient Based on GH-Method: Math-Physical Medicine (No. 540)

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Abstract

Since 5/5/2018, the author has been applying a continuous glucose monitoring (CGM) sensor device on his upper arm that collected and recorded the complete glucose data continuously at 15-minute time intervals on his iPhone. He accumulated 96 glucoses per day over the past ~3.5 years. As a result, over these 1,272 days, he has compiled a total of 122,112 glucose data and stored them in his database where postprandial plasma glucose (PPG) occupies 45,792 data size and 37.5% of the total glucose database.

During 2020-2021 COVID-19 quarantine period, he has a strictly managed routine, without any traveling, which allowed him to have an overall healthy lifestyle. Therefore, all of the 19 influential factors of PPG are mainly control by two primary factors: carbs/sugar intake amount (average at 13.1 gram, low-carb diet) and post-meal waking e excise (average of 4,300 steps).
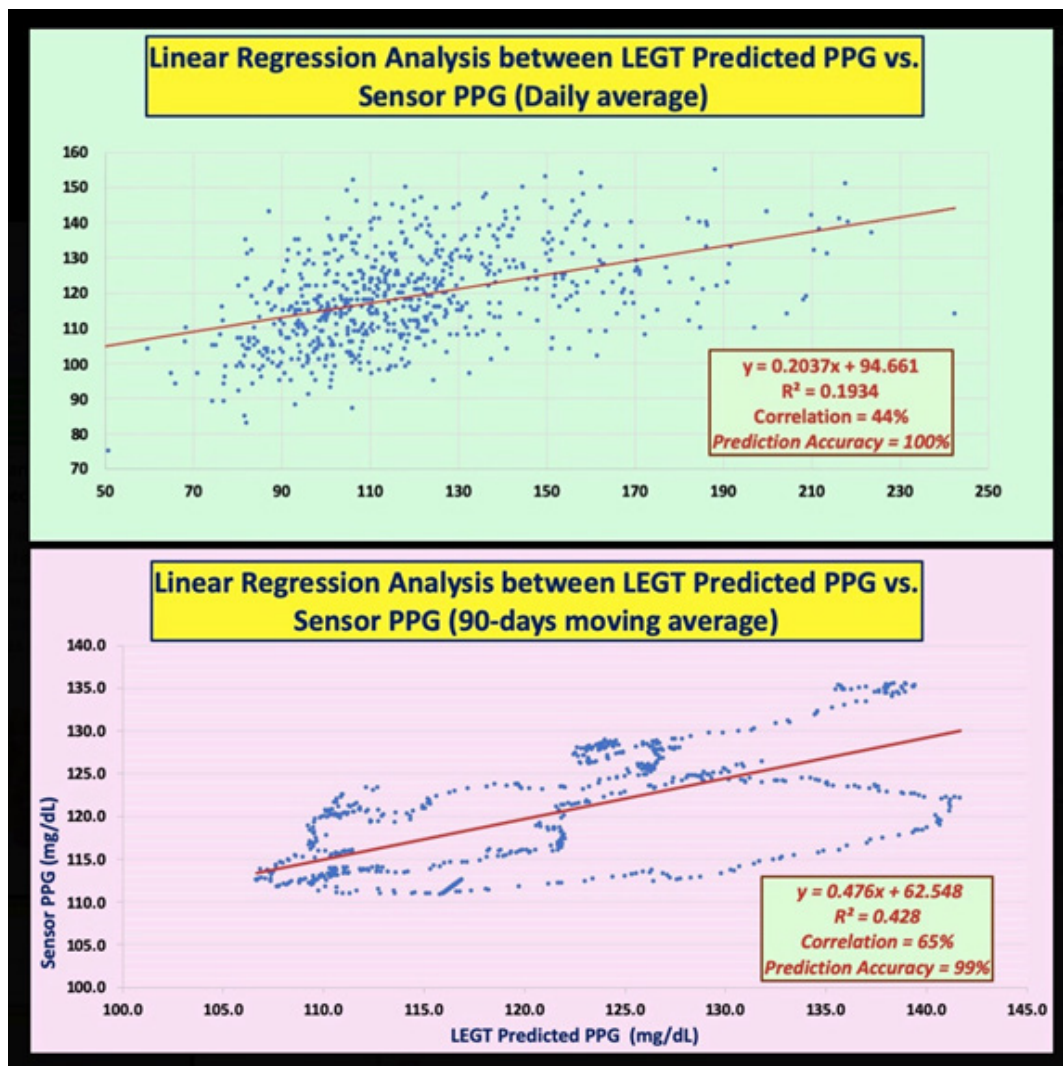
Based on this simplified and healthy lifestyle, he can then easily utilize his developed linear elastic glucose theory (LEGT) model to predict his PPG.

In his previous research reports, he has applied physics concepts and theories, engineering models and equations, mathematical concepts and formulas, computer big data and artificial intelligence (AI) techniques, as well as some statistical approaches. The majority of published medical papers he has read are mainly based on statistics. As a result, in this article, he selected one of the basic statistical tools, linear regression analysis, to study the comparison between his predicted PPG using LEGT and CGM sensor measured PPG.

In conclusion, the linear regression analysis results have provided similar findings with his previous analysis outcomes using other math-physical tools.

There are three specific conclusions worth mentioning:

1. *His predicted PPG utilizing the engineering LEGT model has achieved 99% to 100% of prediction accuracy on both daily PPG dataset and 90-days moving average PPG dataset.*
2. *The "error" or "deviation" of distance between the individual glucose and the red-colored "trend-line" of linear regression model is wider by using the daily PPG data instead of the 90-days moving average PPG (similar to HbA1C). This finding is logical to the author from both biomedical and mathematical viewpoints. Incidentally, this "error" or "deviation" directly relate to the correlation coefficient R and R square.*
3. *Over a reasonable long timeframe, such as 3 months for the HbA1C or 115 days for the red blood cell's lifespan, the deviations can be omitted without any concerns with the accuracy of the HbA1C value, which is the gold standard when treating people with diabetes. This study has revealed a 99% to 100% of predicted PPG accuracy which offers more precise information for clinical treatment of diabetes.*

Linear Regression Analysis between LEGT Predicted PPG vs. Sensor PPG (Daily average)

$$y = 0.2037x + 94.661$$
$$R^2 = 0.1934$$
Correlation = 44%
Prediction Accuracy = 100%

Linear Regression Analysis between LEGT Predicted PPG vs. Sensor PPG (90-days moving average)

$$y = 0.476x + 62.548$$
$$R^2 = 0.428$$
Correlation = 65%
Prediction Accuracy = 99%

Introduction

Since 5/5/2018, the author has been applying a continuous glucose monitoring (CGM) sensor device on his upper arm that collected and recorded the complete glucose data continuously at 15-minute time intervals on his iPhone. He accumulated 96 glucoses per day over the past ~3.5 years. As a result, over these 1,272 days, he has compiled a total of 122,112 glucose data and stored them in his database where postprandial plasma glucose (PPG) occupies 45,792 data size and 37.5% of the total glucose database.

During 2020-2021 COVID-19 quarantine period, he has a strictly managed routine, without any traveling, which allowed him to have an overall healthy lifestyle. Therefore, all of the 19 influential factors of PPG are mainly control by two primary factors: carbs/sugar intake amount (average at 13.1 gram, low-carb diet) and post-meal waking e excise (average of 4,300 steps).

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Methods
MPM Background
To learn more about his developed GH-Method: math-physical medicine (MPM) methodology, readers can read the following three papers selected from his ~500 published medical papers.

The first paper, No. 386 describes his MPM methodology in a general conceptual format. The second paper, No. 387 outlines the history of his personalized diabetes research, various application tools, and the differences between biochemical medicine (BCM) approach versus the MPM approach. The third paper, No. 397 depicts a general flow diagram containing ~10 key MPM research methods and different tools.

In particular, his paper No. 453 illustrates his GH-Method: math-physical medicine in great details, "Using Topology concept of mathematics and Finite Element method of engineering

to develop a mathematical model of Metabolism in medicine in order to control various chronic diseases and their complications via overall health conditions improvement".

The Author'S Case of Diabetes and Complications

The author has been a severe type 2 diabetes (T2D) patient since 1996 and weighed 220 lb. (100 kg, BMI 32.5) at that time. By 2010, he still weighed 198 lb. (BMI 29.2) with an average daily glucose of 250 mg/dL (HbA1C of 10%). During that year, his triglycerides reached to 1161 (diabetic retinopathy or DR) and albumin-creatinine ratio (ACR) at 116 (chronic kidney disease or CKD). He also suffered five cardiac episodes within a decade. In 2010, three independent physicians warned him regarding his needs of kidney dialysis treatment and future high risk of dying from severe diabetic complications. Other than cerebrovascular disease (stroke), he has suffered most known diabetic complications, including both macro-vascular and micro-vascular complications.

In 2010, he decided to launch his self-study on endocrinology, diabetes, and food nutrition in order to save his own life. During 2015 and 2016, he developed four prediction models related to diabetes conditions: weight, PPG, FPG, and A1C. As a result, from using his developed mathematical metabolism index (MI) model in 2014 and the four prediction tools, by end of 2016, his weight was reduced from 220 lbs. (100 kg, BMI 32.5) to 176 lbs. (89 kg, BMI 26.0), waistline from 44 inches (112 cm, nonalcoholic fatty liver disease /NAFLD) to 33 inches (84 cm), average finger glucose reading from 250 mg/dL to 120 mg/dL, and lab-tested A1C from 10% to ~6.5%. One of his major accomplishments is that *he no longer takes any diabetes medications since 12/8/2015.*

In 2017, he has achieved excellent results on all fronts, especially his glucose control. However, during the pre-COVID period of 2018 and 2019, he traveled to approximately 50+ international cities to attend 65+ medical conferences and made ~120 oral presentations. This hectic schedule inflicted damage to his diabetes control, through dinning out frequently, post-meal exercise disruption, jet lag, and along with the overall metabolism impact due to his irregular life patterns through a busy travel schedule; therefore, his glucose control and overall metabolism state were somewhat affected during this two-year heavier traveling period.

During 2020 and 2021 with a strict COVID-19 quarantined lifestyle, not only has he written and published ~400 medical papers in 100+ journals, but he has also reached his best health conditions for the past 26 years. By the beginning of 2021, his weight was further reduced to 165 lbs. (BMI 24.4) along with a 6.1% A1C value (daily average glucose at 105 mg/dL), without having any medication interventions or insulin injections. These good results are due to his non-traveling, low-stress, and regular daily life routines. Due to the knowledge of chronic diseases, practical lifestyle management experiences, and his developed various high-tech tools, they contributed to his excellent health status since 1/19/2020, which is the start date of being self-quarantine.

On 5/5/2018, he applied a CGM sensor device on his upper arm and checks glucose measurements every 5 minutes for a total of ~288 times each day. He has maintained the same measurement pattern to present day. In his research work, he uses the CGM sensor glucose at time-interval of 15 minutes (96 data per day). Incidentally, the difference of average sensor glucoses between 5-minute intervals and 15-minute intervals is only 0.4% *(average glucose of 114.81 mg/dL for 5-minutes and average glucose of 114.35 mg/dL for 15-minutes with a correlation of 93% between these two sensor glucose curves)* during the period from 2/19/20 to 8/13/21.

Therefore, over the past 11 years, he could study and analyze the collected ~3 million data regarding his health status, medical conditions, and lifestyle details. He applies his knowledge, models, and tools from mathematics, physics, engineering, and computer science to conduct his medical research work. His medical research work is based on the aims of achieving both "high precision" with "quantitative proof" in the medical findings.

The following timetable provides a rough sketch of the emphasis of his medical research during each stage:

- 2000-2013: Self-study diabetes and food nutrition, developing a data collection and analysis software.
- 2014: Develop a mathematical model of metabolism, using engineering modeling and advanced mathematics.
- 2015: Weight & FPG prediction models, using neuroscience.
- 2016: PPG & HbA1C prediction models, utilizing optical physics, AI, and neuroscience.
- 2017: Complications due to macro-vascular research such as cardiovascular disease (CVD), coronary heart disease (CHD) and stroke, using pattern analysis and segmentation analysis.
- 2018: Complications due to micro-vascular research such as chronic kidney disease (CKD), bladder, foot, and eye issues such as diabetic retinopathy (DR).
- 2019: CGM big data analysis, using wave theory, energy theory, frequency domain analysis, quantum mechanics, and AI.
- 2020: Cancer, dementia, longevity, geriatrics, DR, hypothyroidism, diabetic foot, diabetic fungal infection, linkage between metabolism and immunity, and learning about certain infectious diseases such as COVID-19.
- 2021: Applications of linear elastic glucose theory (LEGT) and perturbation theory from quantum mechanics on medical research subjects, such as chronic diseases and their complications, cancer, and dementia. Using metabolism and immunity.it's as the base, he expands his research into cancers, dementia, and COVID-19. In addition, he has also developed a few useful analysis methods and tools for his medical research work.

To date, he has collected nearly 3 million data regarding his medical conditions and lifestyle details. In addition, he has written 536 medical papers and published 500+ articles in 100+ various medical journals, including 7 special editions with selected 20-25 papers for each edition. Moreover, he has given ~120

presentations at ~65 international medical conferences. He has continuously dedicated time and effort on medical research work to share his findings and knowledge with patients worldwide.

Stress, Strain, & Young's Modulus

Prior to his medical research work, he was an engineer in the various fields of structural engineering (aerospace, naval defense, and earthquake engineering), mechanical engineering (nuclear power plant equipment, and computer-aided-design), and electronics engineering (computers, semiconductors, and software robot).

The following excerpts come from the internet public domain, including Google and Wikipedia:

"Strain - ε:
Strain is the "deformation of a solid due to stress" - change in dimension divided by the original value of the dimension - and can be expressed as
$\varepsilon = dL / L$
where
ε = strain (m/m, in/in)
dL = elongation or compression (offset) of object (m, in)
L = length of object (m, in)

Stress - σ:
Stress is force per unit area and can be expressed as
$\sigma = F / A$
where
σ = stress (N/m2, lb./in2, psi)
F = applied force (N, lb.)
A = stress area of object (m2, in2)

Stress includes tensile stress, compressible stress, shearing stress, etc.

E, Young's modulus:
It can be expressed as:
E = stress / strain
  $= \sigma / \varepsilon$
  $= (F / A) / (dL / L)$
where
E = Young's Modulus of Elasticity (Pa, N/m2, lb./in2, psi) was named after the 18th-century English physicist Thomas Young.

Elasticity:
Elasticity is a property of an object or material indicating how it will restore it to its original shape after distortion. A spring is an example of an elastic object - when stretched, it exerts a restoring force which tends to bring it back to its original length.

Plasticity:
When the force is going beyond the elastic limit of material, it is

into a "plastic" zone which means even when force is removed, the material will not return back to its original state.

Based on various experimental results, the following table lists some of Young's modulus associated with different materials:

Nylon: 2.7 GPa
Concrete: 17-30 GPa
Glass fibers: 72 GPa
Copper: 117 GPa
Steel: 190-215 GPa
Diamond: 1220 GPa

Young's modules in the above table are ranked from soft material (low E) to stiff material (higher E)."

Highlights of Linear Elastic Glucose Theory

Here is the step-by-step explanation for the predicted PPG equation using linear elastic glucose theory as described below:

1. Baseline PPG equals to 97% of FPG value, or 97% * (weight * GH.f-Modulus).
2. Baseline PPG plus increased amount of PPG due to food, i.e., plus (carbs/sugar intake amount * GH.p-Modulus).
3. Baseline PPG plus increased PPG due to food, and then subtracts reduction amount of PPG due to exercise, i.e., minus (post-meal walking k-steps * 5).
4. The Predicted PPG equals to Baseline PPG plus the food influences, and then subtracts the exercise influences.

The linear elastic glucose equation is:
Predicted PPG = (0.97 * GH.f-modulus * Weight) +(GH.p-modulus * Carbs&sugar) - (post-meal walking k-steps * 5)
Where
1. *Incremental PPG = Predicted PPG - Baseline PPG + Exercise impact*
2. *GH.f-modulus = FPG / Weight*
3. *GH.p-modulus = Incremental PPG / Carbs intake*

Therefore, for this case of pre-period's glucose, the modified equation for predicted pre-period's glucose is listed as below:

Predicted Pre-period's glucose= (FPG * GH.f) + (Carbs/sugar * GH.p) + (walking k-steps * GH.w)
Where
GH.f = 0.97,
GH.p = 3.22,
GH.w = -5.0

Results
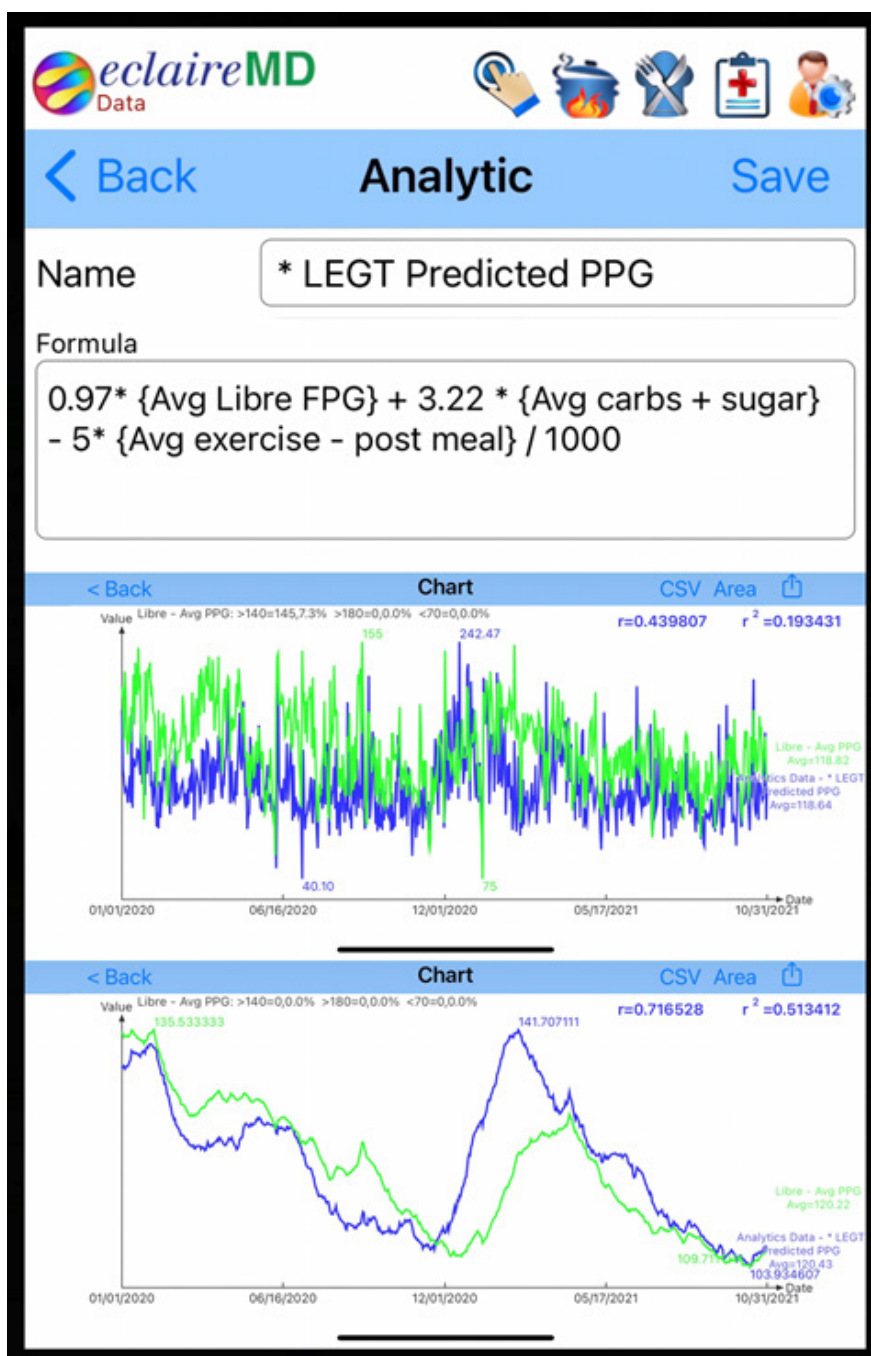Figure 1 combines three time-domain analysis diagrams together.

Figure 1: Time-domain analysis results diagram of both daily PPG and 90-days moving average PPG

The top diagram shows the LEGT equation used for calculating his predicted PPG during the COVID-19 quarantine period from 1/1/2020 to 10/31/2021.

The middle diagram illustrates his daily average PPG time-domain curve (average CGM measured PPG is 118.82 mg/dL and average LEGT predicted PPG is 118.64 mg/dL).

The bottom diagram reflects his 90-days moving average PPG time-domain curve (average CGM measured PPG is 120.22 mg/dL and average LEGT predicted PPG is 120,43 mg/dL).

Figure 1 also demonstrates the linear predicted PPG values achieving a high 99% to 100% prediction accuracy. In addition, from the 90-days moving average curve in the bottom diagram, we can observe the high similarity of two waveforms, LEGT PPG versus CGM PPG.

Figure 2 also combines three linear regression analysis diagrams together.
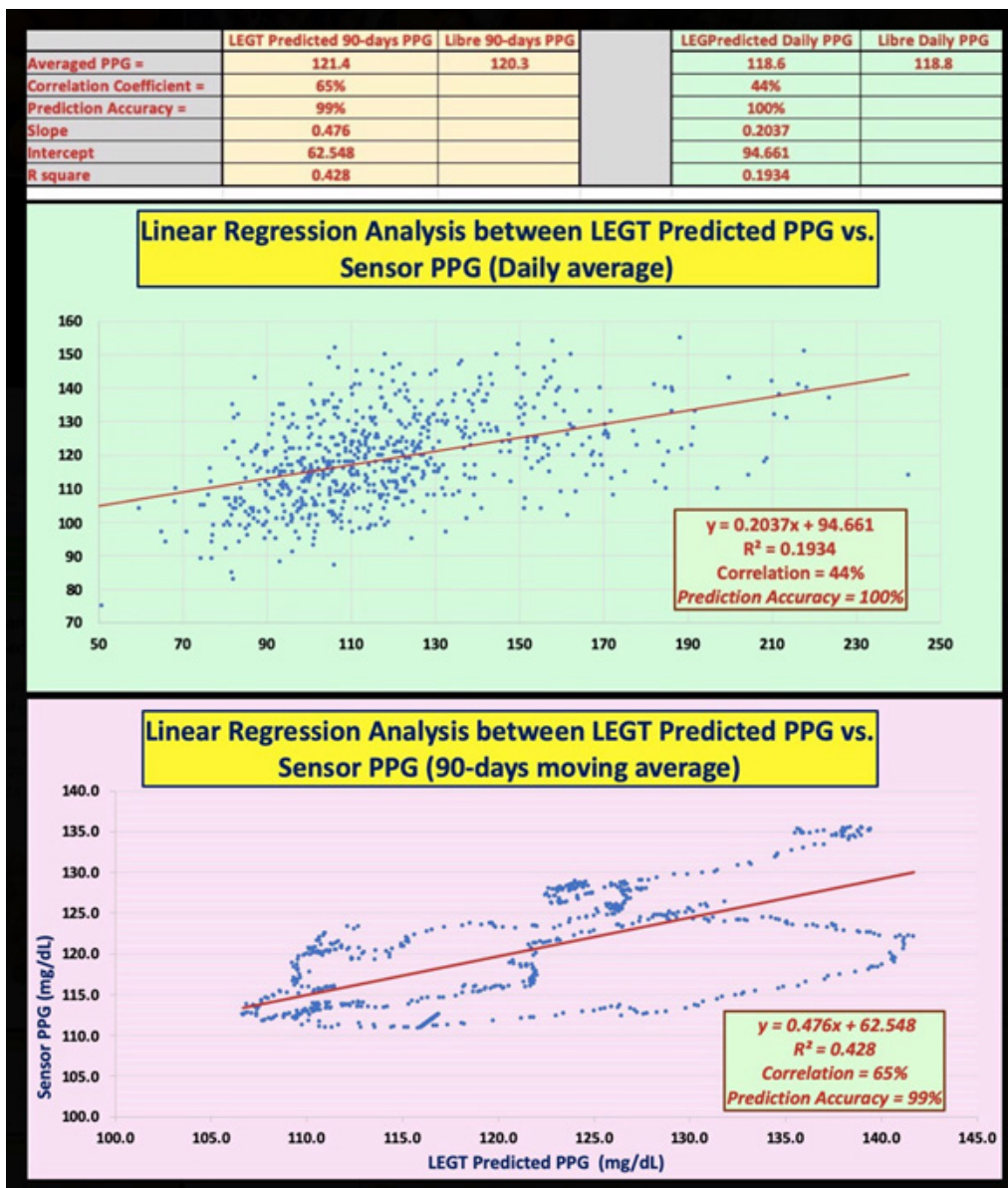
Figure 2: Linear regression analysis results diagram of both daily PPG and 90-days moving average PPG

The top diagram is a data table including the average PPG, correlation, prediction accuracy, and the linear regression formula's 3 characteristics: slope, intercept, and R square.

The middle diagram reflects the linear regression analysis representation which contains the discrete daily PPG data and their red-colored "trend-line".

The bottom diagram displays the linear regression analysis representation which includes the discrete 90-days moving average PPG data and their red-colored "trend-line".

The 90-days moving average data range is shorter and narrower than the discrete daily average PPG dataset because the moving average process has smoothed out the extreme data points. Due to this numerical process, the 90-days moving PPG's linear regression model's R and R square are higher than the daily PPG's linear regression model.

Conclusions
In conclusion, the linear regression analysis results have provided similar findings with his previous analysis outcomes using other math-physical tools.

There are three specific conclusions worth mentioning:

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References

For editing purposes, majority of the references in this paper, which are self-references, have been removed for this article. Only references from other authors' published sources remain. The bibliography of the author's original self-references can be viewed at www.eclairemd.com.

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